MULTI-LEVEL EFFICIENCY ANALYSIS OF OFFSHORE WIND FARM DEVELOPMENT AND OPERATION IN CHINA

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Overview

Amid the transition toward low-carbon energy, the development of offshore wind power has been prioritized by the Chinese government and integrated into the national “Ocean Power” strategy (Chen, 2011; Pan et al., 2020). Over the past decade, China's offshore wind power has undergone high-speed growth followed by deceleration, with its capacity share in total renewable capacity rising from 0.06% to 2.63% in 2010-2021 but declining to 2.29% in 2023. Similarly, the annual contribution of offshore wind power to total renewable energy generation ascended from 0.02% to 4.22% in 2010-2021, while falling to approximately 3.77% in 2023. To regain momentum, it becomes essential to improve the efficiency of offshore wind farm (OWF) development and operation throughout the lifecycle. This raises critical research questions: What are the project-level and provincial-level efficiencies? How does efficiency evolve at the national level? What are the underlying determinants? However, due to limited data availability, no study has systematically evaluated the lifecycle efficiency of OWF development and operation in China, a key player constituting over half of the global installed capacity since 2022 [1]. To address these questions and fill this research gap, this study develops an expanded three-stage output-oriented DEA Model based on detailed data from 117 commissioned OWFs, accounting for over 96% of China’s offshore wind capacity commissioned from 2010 to 2023.

Methods

The output-oriented CCR model calculates the global technical efficiency score for OWFs, using four outputs to represent generated outcomes: average water depth (meters), average distance from shore (kilometers), lifecycle electricity generation (GWh), lifecycle capacity factor (%), and incorporating four inputs to represent utilized resources: total turbine number (count), lifecycle investment (2023 CNY), total subsidies (2023 CNY), and project area (square kilometers). The variable selection adheres to classical DEA principles, seeking input minimization (i.e. less is better) and output maximization (i.e., more is better) under the positivity of all values. By adding a convexity constraint to the CCR model, the BCC model is formulated to measure the local technical efficiency score for OWFs. Based on comparing global technical efficiency with local technical efficiency, scale efficiency can be measured, where the overlap between CCR and BCC frontiers signifies optimality.

To complement the static results from DEA and gauge dynamic changes in efficiency at the national level, a Malmquist Productivity Index (MI) assessment is conducted in the second stage by incorporating the average inputs and outputs of newly commissioned OWFs on an annual basis. Since the derived efficiency scores can be affected by outliers, measurement errors, and specific inputs and outputs within the DEA and MI assessment models, sensitivity analysis is conducted to examine their potential impacts by varying the combinations of input and output variables different from the original model.

Furthermore, to identify the underlying determinants of efficiency scores (i.e., left-censored at 0 and right-censored at 1), the Tobit regression model proposed by Tobin [2] is applied in the third stage. This model incorporates six continuous variables: wind farm size (MW), average turbine capacity (MW), maximum rotor diameter (meters), cumulative installed capacity (GW), knowledge stock (count), and commissioned year. Additionally, three dummy variables are included: substructural type (1 for monopile, and 0 for high-rise pile cap, jacket, and floating foundation), project ownership (1 for “two-grid, five-large, and six-auxiliary” enterprises, and 0 otherwise), turbine brand (1 for China’s top three offshore wind turbine integrated manufacturers, and 0 otherwise).

Results

At the project level, most of the studied OWFs demonstrate favorable technical efficiency, with average CCR and BCC scores of 0.56 and 0.81 respectively. Local technical efficiencies are at least as high as the corresponding global technical efficiencies, on the grounds that the BCC model features a more inclusive efficiency frontier by not imposing constant scale constraints. Under tighter data enveloping, 28 OWFs are classified as efficient with BCC scores exceeding 0.8, considering input-output relationships that vary with scale. However, only 8 OWFs achieve

CCR scores above 0.8, when assuming proportional increases in inputs and outputs. This discrepancy underscores persistent scale inefficiencies in OWF development and operation, with 95 OWFs exhibiting scale efficiency scores below 0.8. This reveals their underutilization of input resources, leading to inconsistent output levels relative to existing technical conditions. To determine whether to scale up or down inputs, the return to scale serves as a useful reference. Around 85% of studied OWFs are examined to have decreasing returns to scale, meaning their outputs increase at a diminishing rate as inputs increase. This suggests their inputs are excessive relative to output levels and should be scaled down to improve efficiency.

At the provincial level, Fujian, Guangdong, Jiangsu, Shandong, and Shanghai exhibit optimal efficiency, as indicated by their positions on the CCR, BBC, and scale efficiency frontiers. Additionally, these provinces maintain relatively balanced technical and scale efficiencies across inputs and outputs, except for Jiangsu, where improved technical efficiency is primarily attributed to increases in distance-from-shore from 2.8 to 72 kilometers in 2010-2023. Comparatively, Liaoning, Zhejiang, and Hebei exhibit lower and highly imbalanced technical and scale efficiencies across inputs and outputs. In Liaoning and Hebei, efficiencies are positively influenced by lifecycle investment and deeper sea, farther-offshore deployments. In Zhejiang and Hebei, one shared dilemma is the scale inefficiency caused by limited nearshore wind resources. Notably, subsidy implementation and area utilization demonstrate favorable efficiencies in Zhejiang.

At the national level, the efficiency of OWF development and operation can be divided into three distinct phases: (1) Wide-range fluctuations during 2010-2016, amid the scheme transition from pilot support to concession bidding and then Feed-in Tariffs (FITs) implementation; (2) Continuous growth in 2017-2019, supported by stable long-term benchmark FITs; (3) Notable declines starting in 2020 under subsidy phase-outs, culminating in a historical low in 2022 following the FITs' termination. In the initial phase, efficiency fluctuations were majorly influenced by lifecycle electricity generation, primarily treated as site selection issues related to available wind resources. In the second phase, efficiency improvements were predominantly affected by project area and the average distance-from-shore, mainly pertaining to the layout of offshore wind turbines. In the third phase, efficiency declines in 2021-2022 were mainly influenced by subsidy implementation, under the elimination of FITs subsidies and their replacement with less efficient provincial subsidies. Additionally, the persistently low efficiency observed in 2022-2023 is largely attributed to the immaturity of farther-offshore technologies.

Technical and scale efficiencies of OWF development are influenced by both drivers and barriers. Key drivers involve economies of scale related to turbine capacity and rotor diameter, learning-by-doing effects from increased capacity installations, and exogenous technological progress over the years. The endogenous learning effect, coupled with exogenous technological progress over the years, enables developers and provinces that delayed OWF commissioning to benefit from late-mover advantages, resulting in higher efficiencies. Despite these drivers, barriers persist, including diseconomies of scale at wind farms, the absence of learning-by-researching effects, and suboptimal ownership structures dominated by "two-grid, five-large, and six-auxiliary" enterprises.

Conclusions

Using detailed data from 117 OWFs commissioned in 2010-2023, this study analyzes the multi-level efficiency of OWFs development and operation in China and investigates the underlying determinants. Key conclusions are drawn: (1) At the project level, favorable technical efficiency but persistent scale inefficiency are largely influenced by investment and electricity generation over the lifecycle. Since inputs in most studied OWF are proven excessive relative to output level, scaling down inputs is necessary to improve efficiency. (2) At the provincial level, Fujian, Guangdong, Jiangsu, Shandong, and Shanghai exhibit higher technical and scale efficiencies in OWF development and operation, compared to Liaoning, Zhejiang, and Hebei, whose efficiencies are primarily constrained by inadequate nearshore wind resources and underdeveloped farther-offshore, deeper-sea technologies. (3) At the national level, the efficiency of OWF development and operation has undergone three distinct phases: A fluctuation phase (2010-2016) during the scheme transition from pilot support to concession bidding and then FITs implementation; A continuous growth phase (2017-2019) supported by stable long-term benchmark FITs subsidies; A notable decline phase (2020-2023) under subsidy phase-outs. Throughout these phases, the priority focus has shifted from site selection to turbine layout, and finally to the utilization of farther-offshore technologies. (4) Technical and scale efficiencies are influenced by both drivers and barriers. Major drivers involve economies of scale related to turbine capacity and rotor diameter, learning-by-doing effects from increased capacity installations, and exogenous technological progress over the years. Nevertheless, barriers persist, including diseconomies of scale at wind farms, the absence of learning-by-researching effects, and suboptimal ownership structures.

References

[1] IRENA, Renewable Energy Statistics 2023, 2023.
[2] J. Tobin, Estimation of relationships for limited dependent variables, Econometrica: journal of the Econometric Society (1958) 24-36.